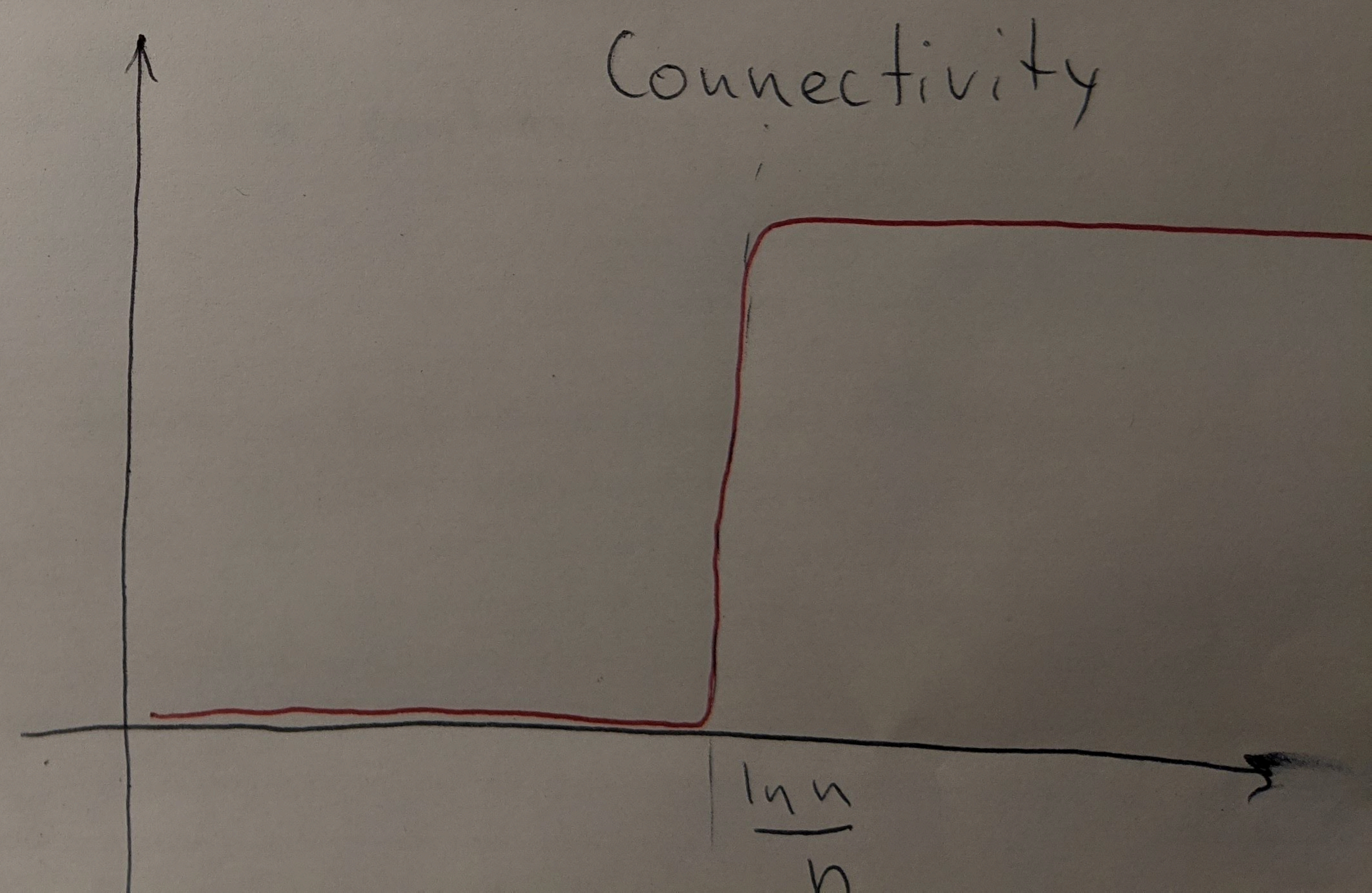
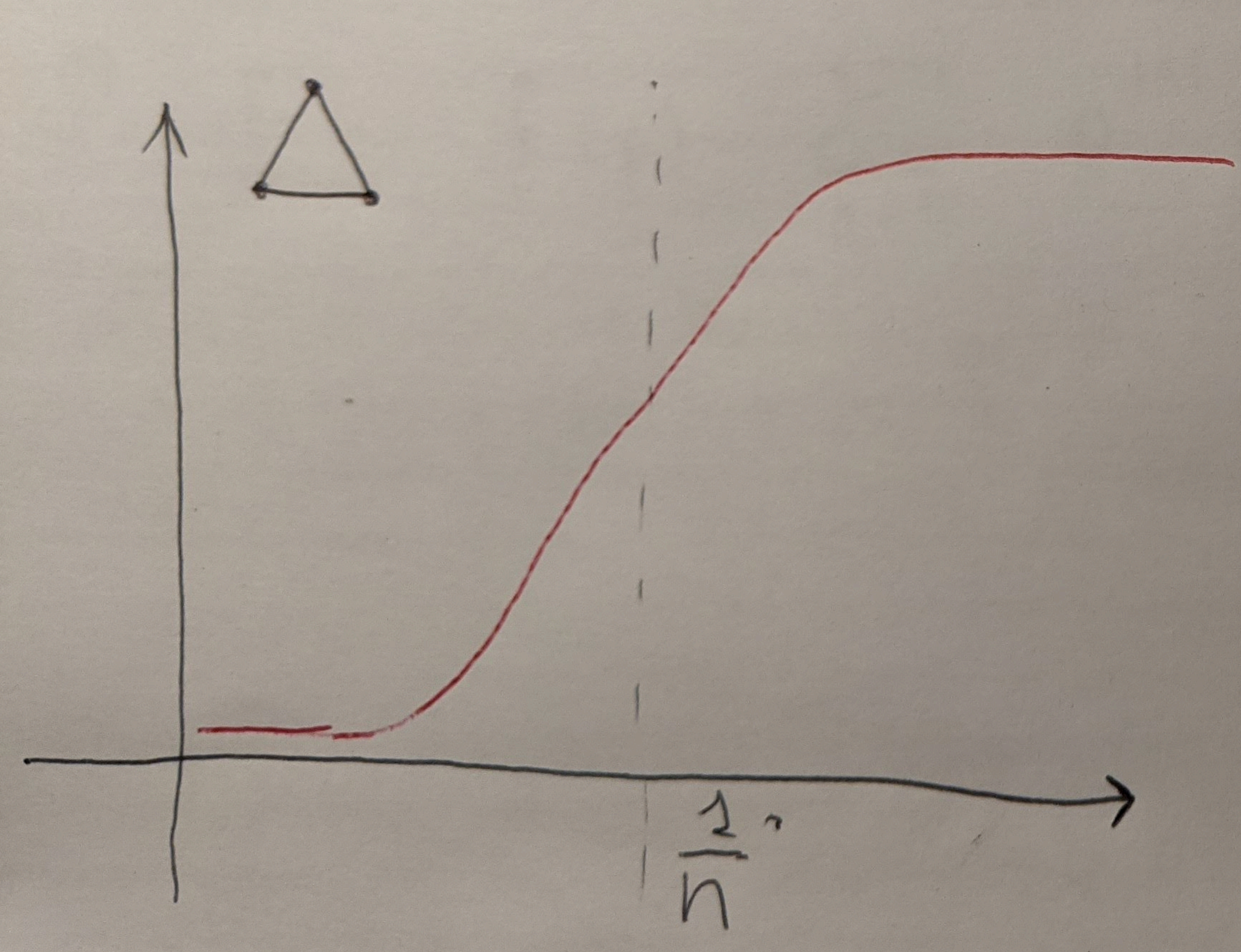


Lecture 8:

Existence of Thresholds & Chernoff Bounds



Previously:

$[n]_p$ - distribution on subsets of $[n] = \{1, 2, \dots, n\}$ obtained by selecting each element at random with probability p .

$\mathcal{P}([n])$
- collection of all subsets of $[n]$.

$\mathcal{F} \subseteq \mathcal{P}([n])$ is **monotone** if for $A \subseteq B \subseteq [n]$ if $A \in \mathcal{F}$ then $B \in \mathcal{F}$.
non-trivial if $\emptyset \notin \mathcal{F}$, $[n] \in \mathcal{F}$.

Lemma 4.6: $\mathcal{F} \subseteq \mathcal{P}([n])$ monotone & non-trivial (for fixed $[n]$)
then $f(p) = \mathbb{P}([n]_p \in \mathcal{F})$
is continuous & increasing.

Proof: $f(p) = \sum_{A \in \mathcal{F}} p^{|A|} (1-p)^{n-|A|} \rightarrow$ continuous.

Increasing \rightarrow by coupling.

$r: [n] \rightarrow [0, 1]$

$(r(1), r(2), \dots, r(n))$ each $r(i)$ is selected indep. uniformly in $[0, 1]$

$[n]_p = \{i : r(i) \leq p\}$.

$p_1 < p_2$ generate (A, B) s.t. $A = \{i : r(i) \leq p_1\}$ $B = \{i : r(i) \leq p_2\}$.
A is distributed according to $[n]_{p_1}$
B is distributed according to $[n]_{p_2}$
and $A \subseteq B$.

$$F(p_1) = \mathbb{P}(A \in \mathcal{F}) \leq \mathbb{P}(B \in \mathcal{F}) = F(p_2)$$

So $F(p)$ is non-decreasing.

With probability > 0 we have $A = \emptyset$, $B = [n]$,
 $\rightarrow (p_2 - p_1)^n$

So $f(p_1) \leq f(p_2) - (p_2 - p_1)^n \rightarrow$ so $f(p)$ strictly increasing.

Lemma 4.7: Let \mathcal{F} , $f(p)$ be as in 4.6.

then $1 - f(2p) \leq (1 - f(p))^2$

Proof: Let A, B be ~~random~~ random subsets of $[n]$ independently selected according to $[n]_p$.

How is $A \cup B$ distributed? $[n]_{2p-p^2}$

$$\mathbb{P}[i \in A \cup B] = 1 - \mathbb{P}[i \notin A] \mathbb{P}[i \notin B] = 1 - (1-p)^2 = \underline{2p-p^2} < 2p.$$

$$F(2p-p^2) = \mathbb{P}(A \cup B \in \mathcal{F}) \geq \mathbb{P}(A \in \mathcal{F} \text{ or } B \in \mathcal{F}) = 1 - (1 - f(p))^2$$

$$\underbrace{F(2p-p^2)}_{\wedge} \quad f(2p) \geq 1 - (1 - f(p))^2 \quad \checkmark$$

Corollary 4.8: Every non-trivial monotone graph property
(Bollobás & Thomason) has a threshold.

1987

Proof: Need to show that there exists for each n

$p_c(n)$ s.t.

$$\mathbb{P}(G(n, p) \in \mathcal{F}) \rightarrow 1 \text{ as } p/p_c \rightarrow \infty \quad (*)$$

$$\mathbb{P}(G(n, p) \notin \mathcal{F}) \rightarrow 1 \text{ as } p/p_c \rightarrow 0. \quad (**)$$

Fix n . $f(p) = \mathbb{P}(G(n, p) \in \mathcal{F})$.

There exists p_c s.t. $f(p_c) = 1/2$. by 4.6.

By 4.7. $1 - f(2^k p_c) \leq (1 - f(p_c))^k = \frac{1}{2^k}$

$$f(2^k p_c) \geq 1 - \frac{1}{2^k} \rightarrow 1 \text{ as } k \rightarrow \infty.$$

implies (*)

is in the other direction

$$1 - f(2^{-k} p_c) \geq (1 - f(p_c))^{1/k} \geq \frac{1}{2^{1/k}}$$

$$f(2^{-k} p_c) \leq 1 - \frac{1}{2^{1/k}} \rightarrow 0 \text{ as } k \rightarrow \infty$$

implies (**).

$\mathcal{F} = G$ has no isolated vertices.

$$(1-p)^n \sim e^{-pn}$$

$$\# \text{ isolated vertices } \sim n e^{-pn} = e^{\log n - pn}$$

Threshold $\frac{\log n}{n}$

$$\text{If } p = \frac{\log n + c(n)}{n}$$

and $c(n) \rightarrow +\infty$

then $G(n, p) \in \mathcal{F}$ w.h.p.

and $c(n) \rightarrow -\infty$

$G(n, p) \notin \mathcal{F}$ w.h.p.

(Same for connectivity)

Sharp threshold

\mathcal{F} has no sharp threshold if there exists $\varepsilon > 0$

and $p_c(n)$ s.t.

$$\mathbb{P}(G(n, p) \in \mathcal{F}) \in [\varepsilon, 1-\varepsilon]$$

for $p \in [(1-\varepsilon)p_c(n), (1+\varepsilon)p_c(n)]$.

~~*~~ K_3 containment or H containment has
no sharp threshold.

but connectivity, existence of Hamiltonian cycles,
have sharp thresholds.

Theorem 4.9: If monotone property \mathcal{F} has no sharp threshold
(Friedgut 1999) then it can be approximated by
a subgraph containment property.

[Another interesting topic:

Thresholds vs. Expectation thresholds.]

5. Chernoff bounds

Theorem 5.1: Let $X = X_1 + X_2 + \dots + X_n$,
 where X_1, X_2, \dots, X_n are independent
 $X_i \in [-1, 1]$, and $E[X_i] = 0$.

$$P(X \geq \lambda \sqrt{n}) \leq e^{-\lambda^2/2}$$

Proof: Moment generating function for X

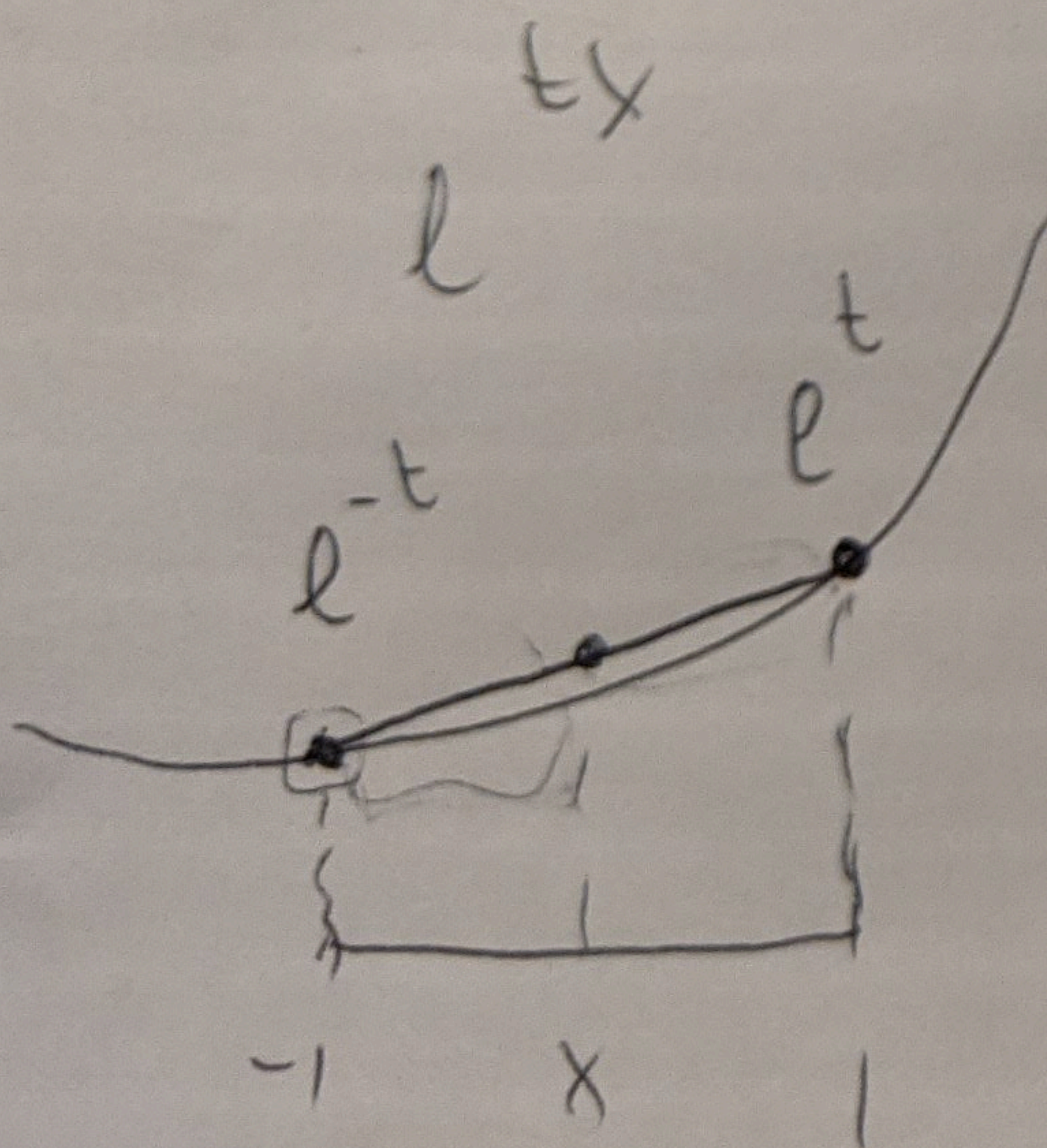
$$t \rightarrow E[e^{tX}] = \sum_{n=0}^{\infty} \frac{t^n}{n!} E[X^n]$$

$$E[e^{tX}] = \prod_{i=1}^n E[e^{tX_i}] \leq e^{\frac{t^2 n}{2}}$$

$$e^{tx} \leq \frac{1-x}{2} e^{-t} + \frac{1+x}{2} e^t \quad \text{by convexity.}$$

$$E[e^{tX_i}] \leq e^{-t} E\left[\frac{1-X_i}{2}\right] + e^t E\left[\frac{1+X_i}{2}\right]$$

$$= \frac{e^t + e^{-t}}{2} \leq e^{\frac{t^2}{2}}$$



↓ exercise?

$$\mathbb{P}(X \geq \lambda\sqrt{n}) = \mathbb{P}\left[e^{tX} \geq e^{t\lambda\sqrt{n}}\right] \leq \frac{\mathbb{E}[e^{tX}]}{e^{t\lambda\sqrt{n}}}$$

Markov

$$= e^{-\underbrace{t\lambda\sqrt{n} + \frac{t^2 n}{2}}_{-\lambda^2/2}} = \underline{e^{-\lambda^2/2}}$$

$$\frac{\partial}{\partial t} = -\lambda\sqrt{n} + tn$$
$$t = \frac{\lambda}{\sqrt{n}}$$

Corollary 5.2: Let $X = X_1 + X_2 + \dots + X_n$, $\mu = \mathbb{E}[X]$
 X_i 's are independent $X_i \in [0, 1]$.

then $\mathbb{P}(X \geq \mu + \lambda\sqrt{n}) \leq e^{-\lambda^2/2}$.